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Operational Performance of Low-cost Carriers and International Airlines: New Evidence Using a Bootstrap Truncated Regression

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Abstract:

Between 2001 and 2005, the US airline industry faced financial turmoil. At the same time, the European airline industry entered a period of substantive deregulation. This period witnessed opportunities for low-cost carriers to become more competitive in the market as a result of these combined events. To help assess airline performance in the aftermath of these events, this paper provides new evidence of technical efficiency for 42 national and international airlines in 2006 using the data envelopment analysis (DEA) bootstrap approach first proposed by Simar and Wilson (J Econ, 136:31–64, 2007). In the first stage, technical efficiency scores are estimated using a bootstrap DEA model. In the second stage, a truncated regression is employed to quantify the economic drivers underlying measured technical efficiency. The results highlight the key role played by non-discretionary inputs in measures of airline technical efficiency.

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Keywords: Data envelopment analysis, efficiency, airlines, bootstrap truncated regression, non-discretionary inputs

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1. Introduction

The motivation for this paper stems from three simultaneous events that took place in the global airline industry between 2001 and 2005. First, the sluggish performance of the US airline industry, which ultimately resulted in net loss of US$40 billion, saw several legacy airlines, including US Airways, United Airlines, Delta, and Northwest, filing for bankruptcy. Under Chapter 11bankruptcy protection, these legacy airlines focused on cost-cutting measures and downsizing operations aimed at improving productivity as part of their restructuring efforts to remain competitive. These efforts had largely paid off by 2006 with the US airline industry overall moving back into the black with a net profit of some US$3 billion (ATA, 2007). Second, this period also witnessed the emergence of US low cost carriers (LCC) as genuine competitors in terms of lower airfares, suggesting the presence of lower cost structures and higher levels of efficiency and productivity. Third, the period 2001–2005 is also associated with a period of intense market volatility associated with the deregulation of the European airline market (Barros and Peypoch, 2009).

This paper contributes to the small extant literature on airline efficiency by focusing on an international comparison of airline performance in 2006. This helps determine whether the affected airlines undertook appropriate cost cutting and operational restructuring in the aftermath of the seismic events of 2001-2005. In addition, the study takes nondiscretionary inputs (i.e. environmental variables) into consideration to help quantify the impact uncontrollable inputs have on measured airline efficiency. As noted by Ouellette and Vierstraete (2004), nondiscretionary inputs are present in virtually all industrial and commercial sectors, even in the long-run, and these must be incorporated into production models so as to correctly measure efficiency. Importantly, few studies of airline performance currently account for environmental variables and these only focus on specific geographic regions.

For instance, Barros and Peypoch (2009) considered the efficiency of European airlines between 2000 and 2005. One contribution of their study was the use of Simar and Wilson's (2007) two-stage approach which permitted the analysis of environmental variables affecting efficiency. Similarly, Bhadra (2009) examined US airlines performance over the period 1985–2006, but using a Tobit model, which Simar and Wilson (2007) had earlier argued, had several limitations. Lastly, Barbot, Costa and Sochirca (2008) assessed the performance of 49 international airlines including LCCs in 2005. While our study may appear similar, a key difference lies in the year of analysis, with our study focusing exclusively on 2006 to best assess the aftermath of the global events of 2001–05. As detailed in ATA (2006, 2007), the US airline industry made a net loss of –US$5.7 billion in 2005 while by 2006 it made a net profit of US$3 billion, thereby suggesting a dramatic turnaround in 2006, the data year of the current study.

In our study, we use the bootstrap truncated regression approach first presented in Simar and Wilson (2007). In the first stage, bootstrapped DEA scores are derived for a sample of 42 airlines in 2006. In the second stage, the estimated efficiencies from the bootstrapping are regressed on the environmental variables (or nondiscretionary inputs) using a truncated regression model. Determining how these environmental variables impact on efficiency is essential for airline management in assessing performance improvement strategies. The objective of the paper is threefold. First, determine if there is evidence of efficiency in legacy airlines in the aftermath of the events of 2001–2005. Second, assess the efficiency levels of LCCs, the legacy airlines, and European airlines when benchmarked against international airlines in 2006: this is an ideal year for assessment as it provides sufficient time for airlines to respond to the industry events in terms of restructuring and the adoption of best-practice management. Finally, estimate the principal economic drivers of the uncontrollable environmental variables underlying measured technical efficiency.

The paper itself comprises five main sections. Section 2 presents the empirical methodology employed. Section 3 describes the inputs and outputs employed and the limitations of the chosen analysis. Section 4 discusses the technical, scale efficiency scores and the regression analysis. The paper ends with some brief concluding remarks.

2. Methodology

Data envelopment analysis (DEA), as developed by Charnes, Cooper, and Rhodes (CCR) in 1978 and later modified by Banker, Charnes and Cooper (BCC) in 1984, build on the frontier efficiency concept first elucidated in Farrell (1957). In general, it is a nonparametric method that measures the efficiency of decision making units (DMUs) and does not require the specification of a specific functional form relating inputs to outputs or the setting of weights for the various factors. DEA thus optimises for each observation an efficient frontier—the maximum output empirically obtainable for any DMU in the observed population given its level of inputs. For a general overview of DEA, see Coelli, Rao and Battese (2005).

However, DEA also assumes that DMUs have full control over inputs, suggesting that such variables are discretionary. This is a major limitation, especially given that Ouellette and Vierstraete (2004) and others have argued that non-discretionary inputs are present in virtually all sectors and that such environmental factors therefore need to be incorporated into any DEA model. Several approaches are found in the literature for handling non-discretionary variables, including work in Banker and Morey (1986), Ray (1991), Ruggiero (1996 and 1998), Muniz (2002), Nemoto and Goto (2003), Bilodeau (2004), Ouellette and Vierstraete (2004), and Essid, Ouellette and Vigeant (2010). From among these, the handling non-discretionary inputs can be broadly categorised into two approaches.

In the first approach, the single-stage model in Banker and Morey (1986) and Ruggiero (1996), among others, directly incorporates non-discretionary input in the DEA program. In the second approach, the multi-stage model, as in Ray (1991), Fried and Lovell (1996), Muniz (2002), and most recently Simar and Wilson (2007), omits the non-discretionary inputs in the initial DEA analysis and then introduces them in non-DEA sequential stages. Simar and Wilson (2007) noted that many studies adopted a two-stage approach whereby DEA scores in the first stage are regressed on covariates (i.e. environmental variables) in the second stage to help handle environmental variables. However, Simar and Wilson (2007) argued that many of these studies in regressing DEA estimates on environmental variables in a two-stage analysis face a key problem in that the DEA efficiency estimates are, by construction, serially correlated. To address this problem, Simar and

Wilson (2007) proposed an alternative estimation and statistical inference procedure based on a double-bootstrap approach. We employ this approach in our analysis.

2.1 *Stage 1 — Data envelopment analysis*

We use the output-oriented variable returns-to-scale (VRS) model to derive efficiency scores. We do this because a constant returns-to-scale (CRS) assumption is only appropriate when firms are operating at their optimal scale, an unlikely situation in an industry where there is considerable evidence of ongoing structural change. Further, imperfect competition and constraints on finance are additional factors associated with firms not operating at their optimal scale, as well evidenced in the US airline industry in the early 2000s operating under Chapter 11 bankruptcy protection and constraints in borrowing. The assumption of VRS also appears appropriate given that our study includes airlines of varying sizes. We assume an output-oriented model consistent with the aim of airlines to maximise revenue from their productive activities. The output-oriented VRS DEA model is expressed as:

$$\hat{\theta}_i = \max_{\theta_{i,\lambda}} \left\{ \theta > 0 \middle| \hat{\theta}_i y_i \leq \sum_{i=1}^{n} y_i\, \lambda;\ \ x_i \geq \sum_{i=1}^{n} x_i\, \lambda;\ \ \lambda \geq 0;\ \sum_{i=1}^{n} \lambda = 1 \right\}, \qquad i = 1, \dots n\ firms$$

where y_i is a vector of outputs, x_i is a vector of inputs, and λ is a I x 1 vector of constants. The value obtained for $\hat{\theta}_i$ is the technical efficiency score for the ith airline. A measure of $\hat{\theta}_i = 1$ indicates that the airline is technically efficient, whereas it is inefficient if $\hat{\theta}_i > 1$. This linear programming problem must be solved *n* times, once for each airline in the sample.

As DEA is sometimes criticized for the potential bias in efficiency estimates and the omission of random error, we employ the bootstrap approach in Simar and Wilson (2007). By combining DEA with bootstrapping technique, we successfully generate a set of bias-corrected estimates of DEA efficiency scores (denoted $\hat{\hat{\theta}}_i$) and confidence intervals that help resolve this problem.

2.2 *Stage 2 — Truncated regression*

The bias-corrected efficiency scores derived from the bootstrap algorithm are then regressed on a set of hypothesized environmental factors using the following regression model:

$$\hat{\hat{\theta}}_i = a + Z_i\delta + \varepsilon_i, \qquad 1 = 1, \dots, n$$

where $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ with left-truncation at $1\text{-}Z_i\delta$; a is a constant term and Z_i is a vector of specific variables for airline *i* that is expected to affect the efficiency of airline performance. The bootstrapping truncated regression algorithm is described in several studies such as Alfonso and Aubyn (2006), Simar and Wilson (2007), Barros and Assaf (2009), and Barros and Barrio (2011) and so we omit details here.

3. Data and specification of inputs and outputs

The data used in the first stage of the procedure are primarily drawn from World Air Transport Statistics (WATS), supplemented with data from RDC Aviations Limited (http://www.rdcaviation.com/). We ensured the consistency of the dataset by verifying the data between both sources. Conceptually, we assume that airline operations utilise inputs, such as labour, to operate a specified number of aircraft that consume fuel to transport a fixed number of passenger seats and freight tonnage over a certain distance. Hence we define four inputs: (i) the average number of employees, (ii) the number of aircraft in the fleet, (iii) fuel burn, and (iv) kilometres flown. In turn, we define two outputs: (i) available seat kilometres (ASK) and (ii) available tonne kilometres (ATK). These two outputs successfully capture the total amount of ASK and ATK produced by each airline and are generally considered as outputs controllable by management as derived from the specified inputs. Alternative indicators, such as revenue passenger kilometres (RPK) and revenue tonne kilometres (RTK), are not considered as outputs in our framework as they are heavily dependent on demand side conditions, circumstances normally beyond the control of airline management (Bhadra, 2009). Moreover, Coelli, Perelman and Romano (1999) argue that the use of tonne kilometres performed bests reflects the ticketing and marketing aspects of airline functions rather than their actual flying operations. We also maintained the DEA convention that the minimum number of DMUs is greater than three times the number of inputs plus outputs [$42 > 3\ (4 + 2)$]. We also draw our data only from scheduled services in order to maintain a consistency in airline operations.

The data used in the second stage regression analysis comprise environmental variables, which are non-discretionary but still expected to have some impact on airline efficiency. Our study includes the following environmental variables: ownership type (i.e. either state-owned or partially state-owned versus privately-owned) as a dummy variable; low-cost versus national airlines (also a dummy variable), along with demand factors including the passenger load factor (PLF) and weight load factor (WLF) as indicators of the ability of firms to behave productively in light of external market pressure on (Bhadra, 2009).

4. Empirical Results

Table 1 presents the bootstrapped technical efficiency scores for the 42 airlines in 2006. As suggested by Simar and Wilson (2007), we replicated the bootstraps two thousand times to fully satisfy coverage of the confidence intervals.

Table 1: Airline efficiency scores, 2006

Airline	Home country	VRS	CRS	Scale efficiency	Returns to scale
Air Canada	Canada	1.1854	1.1918	1.0054	DRS
Air China	China	1.2384	1.2668	1.0229	DRS
Air France	France	1.0000	1.1669	1.1669	DRS
Air India	India	1.0000	1.0140	1.0140	IRS
AirTran Airways (LCC)	US	1.8305	1.9508	1.0657	DRS
Alaska Airlines	US	1.6311	1.6396	1.0052	IRS
America West Airlines	US	1.5743	1.5795	1.0033	IRS
American Airlines	US	1.0000	1.4184	1.4184	DRS
British Airways	UK	1.0557	1.3305	1.2602	DRS
Cathay Pacific	Hong Kong, SAR	1.0000	1.0000	1.0000	CRS
China Eastern Airlines	China	1.0946	1.1293	1.0317	DRS
China Southern Airlines	China	1.1270	1.2287	1.0902	DRS
Continental Airlines	US	1.1338	1.3557	1.1958	DRS
Czech Airlines	Czech Republic	1.3373	1.4013	1.0479	IRS
Delta Airlines	US	1.0185	1.3672	1.3424	DRS
Easyjet (LCC)	UK	1.0670	1.1204	1.0501	DRS
Ethiopian Airlines	Ethiopia	1.4201	1.4819	1.0436	IRS
Frontier Airlines (LCC)	US	1.0000	1.0000	1.0000	CRS
Hawaiian Airlines	US	1.0653	1.1181	1.0495	IRS
IBERIA	Spain	1.4162	1.4188	1.0018	IRS
Japan Airlines	Japan	1.0000	1.0000	1.0000	CRS
Jet Airways	India	1.3115	1.3421	1.0234	IRS
Jet2.Com (LCC)	UK	1.0000	1.0000	1.0000	CRS
Jetblue (LCC)	US	1.0000	1.0000	1.0000	CRS
Korean Air	South Korea	1.0000	1.0000	1.0000	CRS
Lufthansa	Germany	1.0000	1.2561	1.2561	DRS
Malaysian Airlines	Malaysia	1.2162	1.2214	1.0043	IRS
Mesa Airlines (LCC)	US	1.0000	1.0000	1.0000	CRS
Northwest Airlines	US	1.2226	1.6145	1.3205	DRS
Oman Air	Oman	1.0000	1.3448	1.3448	IRS
Pakistan International Airlines	Pakistan	1.2086	1.2389	1.0250	IRS
Qantas Airways	Australia	1.0826	1.1179	1.0326	DRS
SATA Internacional	Portugal	1.0000	1.5855	1.5855	IRS
SAS Scandinavian Airlines	Sweden	1.3906	1.4257	1.0252	DRS
Singapore Airlines	Singapore	1.0000	1.0000	1.0000	CRS
Southwest Airlines (LCC)	US	1.1605	1.7848	1.5379	DRS
Spanair	Spain	1.3484	1.3843	1.0266	IRS
Srilankan Airlines	Sri Lanka	1.0000	1.0798	1.0798	IRS
Swiss International Airlines	Switzerland	1.3118	1.3256	1.0105	IRS
Thai Airways	Thailand	1.0000	1.0000	1.0000	CRS
United Airlines	US	1.0000	1.5113	1.5113	DRS
US Airways	US	1.6181	1.6472	1.0180	DRS

As shown in Table 1, airlines with a technical efficiency score of unity are operating efficiently and lie on the carrier production frontier in 2006. Under VRS, seventeen airlines are then technically efficient as a result of management skill. Of these seventeen airlines, only nine are scale efficient: that is, operating at an appropriate scale of operations (neither too big or too small). These include Asian airlines, such as Cathay Pacific, JAL, Korean Airlines, Singapore Airlines and Thai Airways, along with some of the LCCs, including Frontier Airlines, Jet2.com and Jetblue and Mesa Airlines. Measures of scale efficiency are calculated using the ratio of efficiency scores of CCR/BCC (Banker, 1984). As pointed out by Gollani and Roll (1989), CCR under CRS measures overall efficiency which is made up of pure technical efficiency and scale efficiency, while BCC under VRS measures only pure technical efficiency and excludes scale effects.

In terms of explaining the measures of efficiency, in Europe, deregulation and liberalisation effectively opened up the airline industry, and this created intense competition between 2001 and 2005. While airlines such as Air France, SATA Internacional and Lufthansa have shown to adopt best-practice management as indicated in their VRS efficiency scores, their scale of operations as indicated by their returns to scale is too large. This suggests that deregulation has had a larger impact on the major national airlines. Of European airlines, only Jet2.com achieved both technical efficiency and scale efficiency. Overall, airlines with DRS (decreasing returns-to-scale) display a scale of operations that is too large for industry circumstances and should be down-sized. This suggests that market power of Air France, British Airways, Lufthansa, and Scandinavian Airlines has been competed away by its competitors, largely from the opening up of the airline industry.

In contrast, airlines such as Iberia, SATA Internacional, Spanair and Swiss International Airlines with IRS (increasing returns-to-scale) suggest that competition has opened up opportunities for these airlines to expand their operations and achieve better economies of scale. In the US, American Airlines, Frontier Airlines, JetBlue, Mesa Airlines and United Airlines were technically efficient through best-practice management. In terms of scale of operations, only Frontier Airlines, JetBlue and Mesa Airlines were efficient. Based on the events surrounding the US airline industry between 2001 and 2005, the results suggest that while airlines were adopting best-practice management through cost-cutting measures, the restructuring in operations took a longer time to have any discernible impact on scale efficiency. We can see this most clearly in the returns-to-scale with the US legacy airlines (American Airlines, Continental, Delta, United Airlines and US Airways) suggesting that their scale of operations were too large for the market, thus demanding the need to down-size their operations to remain competitive.

The inclusion of the Asian airlines provide a useful benchmark for the US and European airlines which detects poorly performing airlines. In turn, benchmarks provide ways for such airlines to improve on management and operations. To test the validity of the Asian airlines as benchmarks, DEA was also employed to the same sample of airlines excluding the Asian airlines which were efficient. The results (not shown but available on request) showed most of the European airlines and US airlines were technically efficient. Hence, the results suggest that omission of Asian airlines can provide exaggerated efficiency scores thus indicating that appropriate performance measurement of airlines require the inclusion of non-US and non-European airlines.

Table 2: Bootstrapped efficiency results, 2006 (VRS)

DMU	$\hat{\theta}_i$	$\hat{\hat{\theta}}_i$	$b\widehat{ia}s$	Standard error	Lower bound	Upper bound
Air Canada	1.1854	1.2975	-0.0728	0.0031	1.1902	1.4237
Air China	1.2384	1.3376	-0.0598	0.0013	1.2453	1.4245
Air France	1.0000	1.0902	-0.0827	0.0022	1.0046	1.1505
Air India	1.0000	1.1060	-0.0958	0.0029	1.0064	1.1754
AirTran Airways (LCC)	1.8305	1.9743	-0.0397	0.0006	1.8426	2.1110
Alaska Airlines	1.6311	1.7400	-0.0383	0.0004	1.6404	1.8322
America West Airlines	1.5743	1.6689	-0.0360	0.0004	1.5833	1.7677
American Airlines	1.0000	1.2180	-0.1789	0.0202	1.0069	1.3264
British Airways	1.0557	1.1422	-0.0717	0.0016	1.0616	1.2079
Cathay Pacific	1.0000	1.1461	-0.1275	0.0083	1.0072	1.2682
China Eastern Airlines	1.0946	1.1655	-0.0555	0.0011	1.1014	1.2274
China Southern Airlines	1.1270	1.1813	-0.0408	0.0009	1.1310	1.2522
Continental Airlines	1.1338	1.2271	-0.0670	0.0014	1.1416	1.2995
Czech Airlines	1.3373	1.4055	-0.0363	0.0003	1.3459	1.4594
Delta Airlines	1.0185	1.1171	-0.0866	0.0031	1.0250	1.2005
Easyjet (LCC)	1.0670	1.1377	-0.0581	0.0015	1.0728	1.2162
Ethiopian Airlines	1.4201	1.5074	-0.0407	0.0005	1.4280	1.5843
Frontier Airlines (LCC)	1.0000	1.2350	-0.1903	0.0272	1.0061	1.3742
Hawaiian Airlines	1.0653	1.1469	-0.0667	0.0012	1.0722	1.2015
IBERIA	1.4162	1.5392	-0.0564	0.0014	1.4237	1.6491
Japan Airlines	1.0000	1.1723	-0.1469	0.0098	1.0045	1.2623
Jet Airways	1.3115	1.3791	-0.0374	0.0003	1.3203	1.4314
Jet2.Com (LCC)	1.0000	1.2446	-0.1964	0.0337	1.0064	1.4116
Jetblue (LCC)	1.0000	1.1264	-0.1122	0.0036	1.0061	1.1751
Korean Air	1.0000	1.1823	-0.1542	0.0117	1.0059	1.2760
Lufthansa	1.0000	1.1201	-0.1072	0.0034	1.0074	1.1843
Malaysian Airlines	1.2162	1.3129	-0.0604	0.0011	1.2243	1.3885
Mesa Airlines (LCC)	1.0000	1.2419	-0.1948	0.0337	1.0066	1.4114
Northwest Airlines	1.2226	1.3344	-0.0684	0.0015	1.2306	1.4223
Oman Air	1.0000	1.1559	-0.1348	0.0083	1.0066	1.2587
Pakistan International Airlines	1.2086	1.3092	-0.0635	0.0014	1.2149	1.3873
Qantas Airways	1.0826	1.1850	-0.0798	0.0026	1.0903	1.2804
SATA Internacional	1.0000	1.2606	-0.2067	0.0367	1.0075	1.4148
SAS Scandinavian Airlines	1.3906	1.4839	-0.0452	0.0007	1.3974	1.5694
Singapore Airlines	1.0000	1.2247	-0.1834	0.0267	1.0044	1.3604
Southwest Airlines (LCC)	1.1605	1.2356	-0.0523	0.0011	1.1677	1.3167
Spanair	1.3484	1.4263	-0.0405	0.0003	1.3554	1.4797
Srilankan Airlines	1.0000	1.1291	-0.1142	0.0058	1.0062	1.2265
Swiss International Airlines	1.3118	1.4120	-0.0540	0.0008	1.3201	1.4806
Thai Airways	1.0000	1.1342	-0.1183	0.0044	1.0063	1.1912
United Airlines	1.0000	1.1621	-0.1394	0.0096	1.0057	1.2671
US Airways	1.6181	1.7696	-0.0528	0.0016	1.6231	1.9205

Table 2 presents the bias-corrected efficiency scores and the original unadjusted DEA scores for comparison. Importantly, when considering the bias-corrected efficiency scores, none of the airlines appear close to the frontier. Accordingly, as the bias is large relative to the variance in every case, the bias-corrected efficiency scores are preferred to the original estimates (Simar and Wilson, 1998). Furthermore, the bias-corrected efficiency scores are also preferred over the original DEA scores given the former are within the lower and upper bounds of the DEA bootstrap confidence intervals whereas the latter do not indicate biasness in the original estimates.

In order to examine the hypothesis that environmental variables of a non-discretionary nature have a significant impact on measured airline efficiency, we follow the two-step approach, as suggested by Coelli, Rao and Battese (1998). It is well documented in the DEA literature that the efficiency scores obtained in the first stage are correlated with the explanatory variables used in the second stage, which makes the second-stage estimates inconsistent and biased. A bootstrap procedure is needed to overcome this problem (Efron and Tisbhirani 1993). Hence, following Simar and Wilson (2007) bootstrap approach, the estimated specification for the regression is expressed as:

$$\hat{\hat{\theta}}_i = \beta_0 + \beta_1 Ownership_i + \beta_2 LCC_i + \beta_3 PLF_i + \beta_4 WLF_i + \varepsilon_i$$

where $\hat{\hat{\theta}}_i$ is the bootstrapped bias-corrected efficiency score, LCC is a low cost carrier, PLF is the passenger load factor and WLF is the weight load factor.

Given that the analysis is output-oriented which indicates efficiency score θ ranging from 1 to infinite, any value higher than θ indicates inefficiency. Thus, variables with an estimated positive (negative) coefficient have a negative (positive) impact on efficiency.

Table 3: Truncated Regression

Variable	Coefficient	Confidence Interval	
		Lower bound	Upper bound
Constant	1.93301* (0.47295)	0.9990	2.8530
Ownership	0.07314* (0.07056)	-0.0645	0.2121
LCC	-0.01250* (0.12897)	-0.2687	0.2368
PLF	-0.00649* (0.00699)	-0.0210	0.0065
WLF	-0.00296* (0.00378)	-0.0094	0.0054

* Significant at 5% confidence interval; standard errors are shown in parenthesis; total number of iterations = 2000.

Using the second-stage regression analysis, the results shown in Table 3 suggest that environmental variables have a significant impact on the technical efficiency of airlines. Of the environmental variables, LCC, PLF and WLF have a positive impact on efficiency. That is, LCC contributes positively to efficiency, which suggests that being a low-cost carrier enhances their ability to transform inputs into outputs efficiently, as driven by their incentive to remain competitive by adopting best-practice management and operations. PLF and WLF also contribute positively to efficiency suggesting that demand factors, which are outside management control, also provide external market pressure on airlines to perform productively. This accords with similar findings in Bhadra (2009). Finally, ownership however contributes negatively to efficiency which might suggest that state-owned/quasi-state owned airlines benefit from government subsidies which could adversely influence productivity especially when the market is volatile and unpredictable. One would then expect private airlines to be more efficient than state-owned in the long run when the market settles down and returns to normalcy.

5. Conclusion

In this paper, a DEA double bootstrapping model as proposed by Simar and Wilson (2007) was employed to measure technical efficiency of a sample of LCCs and international airlines for the year 2006. Bootstrap DEA scores derived in the first-stage analysis are estimated simultaneously with a bootstrapped truncated regression model to explain efficiency drivers.

Benchmarks in the form of non-US and non-European international airlines are considered since these airlines are not affected by the events that occurred in these regions. That said, the results do suggest that the non-US and non-European international airlines, mainly the Asian airlines, do perform at efficient levels which provides a benchmark for poorly performing airlines to find ways to improve their management and operations. Generally, the efficiency scores of the US airlines and European airlines suggest that the LCCs played a significant role in intensifying airline competition. For the US legacy airlines and some of the major European airlines to remain competitive in the future, they need to scale-down their operations since the current levels are no longer sustainable as a result of LCCs becoming more competitive in the market. In the second stage analysis, the results do justify that LCCs and demand factors such as PLF and WLF have a significant impact on efficiency levels. On the other hand, there is insufficient evidence to prove ownership contributing to efficiency.

The contribution of this paper to the literature of airline efficiency is the assessment of the performance of international airlines for the period after events of deregulation in the European airline industry and financial turmoil in the US airlines. By combining DEA approach with the Simar and Wilson (2007) double-bootstrap truncated regression method, an econometric analysis enables better explanation of drivers of efficiency while simultaneously producing standard errors and confidence intervals for these scores.

References

Air Transport Association of America (ATA), (2006). *Economic Report.* Washington, DC. www.airlines.org

Air Transport Association of America (ATA), (2007). *Economic Report*. Washington, DC. www.airlines.org

Banker, R.D. (1984). Estimating most productive scale size using data envelopment Analysis. *European Journal of Operational Research*, *17*, 35–44.

Banker, R.D., and Morey, R.C. (1986). Efficiency Analysis for Exogenously Fixed Inputs and Outputs. *Operations Research*, *34*, 513-521.

Barbot, C., Costa, A., and Sochirca, E. (2008). Airlines performance in the new market context: A comparative productivity and efficiency analysis. *Journal of Air Transport Management*, *14*, 270-274.

Barros, C.P., and Assaf, A. (2009). Bootstrapped efficiency measures of oil blocks in Angola. *Energy Policy*, *37*, 4098–4103.

Barros, C.P., and Garcia-del-Barrio, P. (2011). Productivity drivers and market dynamics in the Spanish first division football league. *Journal of Productivity Analysis*, *35*, 5-13.

Barros, C.P., and Peypoch, N. (2009). An evaluation of European airlines' operational performance. *International Journal of Production Economics*, *122*, 525-533.

Bhadra, D. (2009). Race to the bottom or swimming upstream: Performance analysis of US airlines. *Journal of Air Transport Management*, *15*, 227–235.

Bilodeau, D., Crémieux, P.-Y., Jaumard, B., Ouellette, P., and Vovor, T. (2004). Measuring Hospital Performance in the Presence of Quasi-Fixed Inputs: An Analysis of Québec Hospitals. *Journal of Productivity Analysis*, *21*, 183–199.

Coelli, T., Perelman, S., and Romano, E. (1999). Accounting for Environmental Influences in Stochastic Frontier Models: With Application to International Airlines. *Journal of Productivity Analysis*, *11*, 251–273.

Coelli, T., Rao, D.S.P., and Battese, G.E. (2005) *An Introduction to Efficiency and Productivity Analysis*. (2nd ed.). Springer, Boston.

Efron, B., and Tisbhirani, R.J. (1993). *An introduction to the bootstrap*. Chapman & Hall, New York.

Essid, H., Ouellette, P., and Vigeant, S. (2010). Measuring efficiency of Tunisian schools in the presence of quasi-fixed inputs: A bootstrap data envelopment analysis approach. *Economics of Education Review*, *29*, 589–596.

Farrell, M.J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society, Series A*, *120*, 253–290.

Golany, B., and Roll, Y. (1989). An application procedure for DEA. *Omega: The International Journal of Management Science*, *17*, 237–250.

Mũniz, M.A. (2002). Separating managerial inefficiency and external conditions in data envelopment analysis. *European Journal of Operational Research*, *143*, 625–643.

Nemoto, J., and Goto, M. (2003). Measurement of Dynamic Efficiency in Production: An Application of Data Envelopment Analysis to Japanese Electric Utilities. *Journal of Productivity Analysis*, *19*, 191–210.

Ouellette, P., and Vierstraete, V. (2004). Technological change and efficiency in the presence of quasi-fixed inputs: A DEA application to the hospital sector. *European Journal of Operational Research*, *154*, 755–763.

Ray, S.C. (1991) Resource-Use Efficiency in Public Schools. A Study of Connecticut Data. *Management Science*, *37*, 1620-1628.

Ruggiero, J. (1996). On the measurement of technical efficiency in the public sector. *European Journal of Operational Research*, *90*, 553-565.

Ruggiero, J. (1998). Non-discretionary inputs in data envelopment analysis. *European Journal of Operational Research*, *111*, 461-469.

Simar L., and Wilson, P. (1998). Sensitivity analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. *Management Science*, *44*, 4–61.

Simar L., and Wilson, P. (2007). Estimation and inference in two-stage, semi-parametric models of productions processes. *Journal of Econometrics*, *136*, 31–64.